Machine Learning Techniques Integrated in Robotics, Electrical and Electronics Engineering, And IoT Devices.

PORAM TARUN PRAKASH[1], P. SATYANARAYANA RAO[2]
[1] *Department of Electronics and Communication Engineering, AU college of Engineering(A), Andhra University, Visakhapatnam, India*
[2] *Assistant Professor, Department of Physics, Maharajah's College(A), Vizianagaram, India*

Abstract- This paper aims to find the best machine-learning technique used for integration in robotics, electrical and electronics engineering, and IoT devices. We investigated different recurrent neural networks such as LSTM, BiLSTM, and GRU for combination with Convolution neural networks. We experimented with three different categories related to robotic arms, electrical circuits, and IoT-based smart agriculture. Models are evaluated based on Precision, recall, and F1 score. Finally, we conclude combination of a convolution neural network and a bi-directional long short-term memory model performs well for different predictions.

Indexed Terms- Deep Learning, Electrical Systems, Electronics, IoT, Machine Learning, Robotics

I. INTRODUCTION

In recent times, many organizations have included machine learning techniques in robotics and electrical systems. This improvement leads to some of the research questions below:

1. How can we automate machines using machine learning techniques?
2. What areas of industries can we automate?
3. Is there a common model that can work in different sectors?

II. PREVIOUS WORKS

A. Integration of Robotic Computer Vision with Machine learning.

Mahajan et al.[1] decided to introduce a Long-Term short-memory (LSTM) classifier for the movement of robots. This research utilizes the captured movements to train the robot to make accurate predictions of the movement in the path. However, the model is not evaluated vastly in the Real world.

B. Integration of Sensor data preprocessing with Machine learning.

Kang et al.[2] designed a door system using a displacement sensor and machine learning techniques to prevent traffic congestion. However, the research is limited to pneumatic door systems in EMU's.

C. Integration of Movement of Robotic arm with Machine learning.

Huang et al.[3] focuses on improving velocity planning by using a reinforcement learning algorithm. However, the study focuses on the simulation-based evaluation, which may vary in real-time.

Rodrigues et al.[4] proposes a framework for predicting robotic arm movements and aiming to mitigate risks in industrial environments. However the framework depends on a single camera, and this can be still predicted inaccurately

.

D. Integration of Smart Grid Mangement with Machine learning.

Ganesh et al.[5] proposed a novel framework for energy management for IoT-enabled smart grid systems. This framework utilizes the Stacked convolution Bi-Directional Gated Attention network for accurate energy load estimation. However, still, the model faces challenges due to abrupt changes in extreme events such as weather events.

E. Integration of Fault detection with Machine learning.

Al-kaf et al.[6] ensemble machine learning for fault detection in circuits. It detects open circuit faults in inverters, using machine learning techniques such as

Random Forest. However, the model might not capture all the complexities encountered in the real-world.

F. Integration of Circuit design optimization with Machine learning.

Dai et al.[7] acknowledges the demand for deep learning models in IC design optimization. However, the paper lacks the benchmarks.

G. Integration of edge computing with Machine learning.

Xu et al.[8] proposed a virtual machine placement VMP algorithm in mobile edge computing. This VMP algorithm uses a migration mechanism to generate efficient virtual machine placement decisions.

H. Integration of Agriculture with Machine learning.

Attri et al.[9] provided a detailed overview of various machine learning models, including decision trees, support vector machines, etc.

I. Integration of Smart City solutions with Machine learning.

Ullah et al.[10] provides us with information about an overview of various smart city applications with implement IOT and machine learning.

III. METHODOLOGY

To know the best model that fits almost all types of IoT, robotics, and electrical and electronic systems, we propose our base model as the CNN model, which can capture the features using its layers. Further recurring neural networks are combined for further enhancement. So in Subsections A, B, and C, the details of the experiments in different sectors such as IoT, robotics, and electrical and electronic systems are discussed. This discussion involves in collection of datasets, training and validation, and experimental results of the different combinations of models.

A. Robotic Arm Movement Prediction

*The (*robotic_arm_dataset_multiple_trajectories) is a repository in Kaggle that represents the different data points of the robotic hand. We labeled the data based on the turning of the robotic hand. The data is used for training the model. Some points are used for validation and testing.

The following Figure 1 has coordinates adjusting the robot hand turned towards the right side so we labelled this robotic hand turned towards Right. The opposite coordinates of the robotic arm are labeled as the Left side.

Our experiment includes, classification of the movement of the robotic arm using a convolution neural network with a combination of recurrent neural networks. The results are discussed in experimental results section.

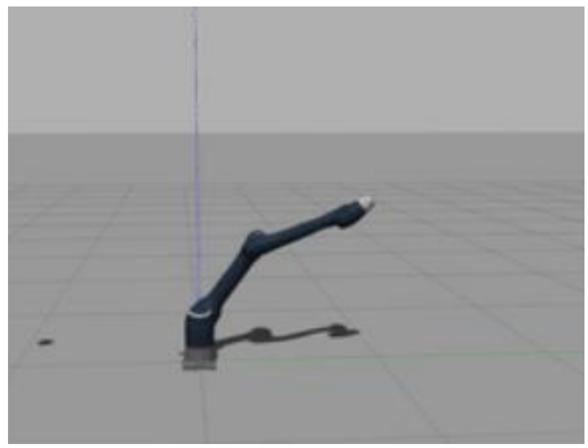

Figure 1 : Robotic hand turned towards Right side

B. Fault detection in Electrical Circuits

The experiment uses a dataset from Kaggle named Electrical Wiring Faults Detection. The dataset contains images of CPU in aviation. About 300 images are captured by a trained veteran with a Canon S95 Power shot camera. There are 300 labels with 300 images. Labels positioning the fault in an electrical circuit. Predicting the exact location of the fault can be too difficult with a small dataset of 300 images. So we considered increasing the size of the predicted square by 0.2cm. This means, even if the model predicts at 0.2cm far, it may result in an accurate prediction.

We used a basic model as convolution neural networks and combined it with different recurrent neural networks to find the fault. The results are discussed in the Experimnetal results section.

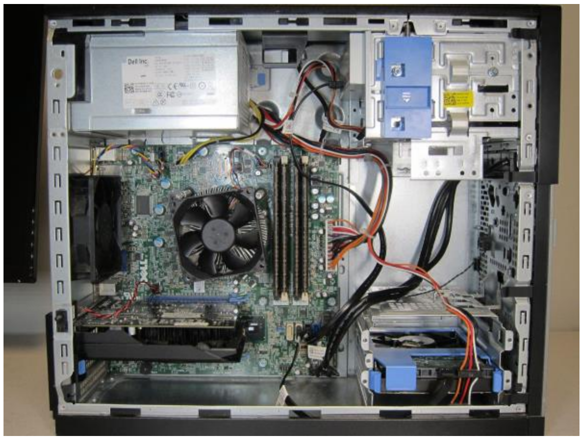

Figure 2: Normal Circuit

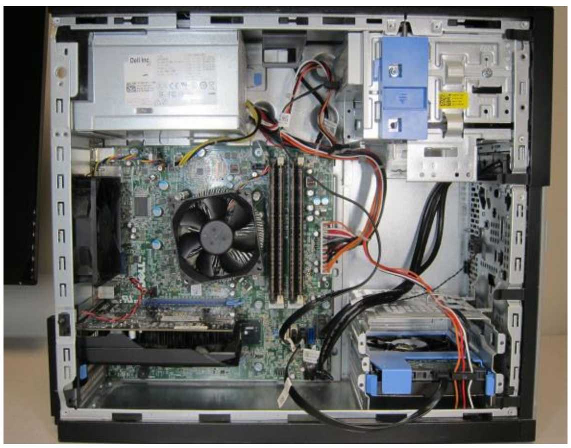

Figure 3: Misrouted Circuit

Figure 4: Disconnected Circuit

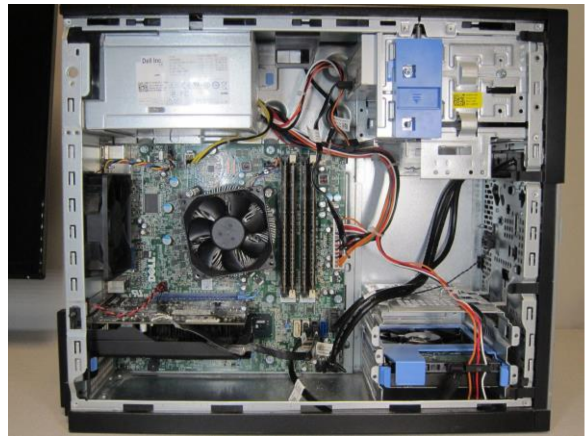

Figure 5: Damaged Circuit

The dataset is made up of three different sections they are training images, validation images, and testing images. Further, they are classified based on different configurations such as disconnection of SATA cables or configuration of power supply units.

The Figures 2,3,4,5 are Normal, Misrouted, Disconnected, and Damaged circuits. For example, we can observe that the SATA cables in figure 4 in the bottom-right are disconnected.

C. IOT enabled Smart Agriculture for crop health monitoring

The dataset is collected from the Kaggle website from a repository named PlantVillage dataset. It contains different types of leaves of Potato, Pepper, and Tomato plants. The leaves of Potato are classified into different categories they are:

1. Healthy
2. Early blight
3. Late blight

The leaves of Pepper are classified into different categories they are:

1. Healthy
2. Bacteria

The leaves of Tomatoes are classified into different categories they are:

1. Healthy
2. Early blight

3. Late blight
4. Bacterial spot
5. Leaf Mold
6. Septoria leaf spot
7. Spider mites
8. Target spot
9. Mosaic virus
10. Yellow Leaf

So we stratified the dataset for training, validation, and testing while maintaining the categories of the following plant's leaves. The following Figure 7,8,9 shows different types of Potato leaves with different diseases.

Then we trained the dataset with different combinations convolution and recurrent neural networks. The results are shown in the Experimental results section.

Figure 6: Healthy Potato leaf

Figure 7: Potato with Early blight

Figure 8: Potato with Late blight

IV. EXPERIMENTAL RESULTS

The experimental results of the above experiments are discussed in this section. We considered different Recurrent neural networks in combination with convolution neural networks. The Recurrent neural networks include LSTM, BiLSTM, and GRU. The metrics such as Precision, Recall, and F1 score are calculated.

We have trained the models with different hyperparameters such as changing learning rates, optimizers, and other reduction of overfitting techniques.

The precision of the above-mentioned experiments is discussed in the Table 1.

Experiment Name	CNN+ LSTM	CNN+ BiLSTM	CNN+ GRU
a)Robotic arm Movement	0.95	0.94	0.95
b)*Fault detection in Electrical Circuits*	0.25	0.43	0.25
c) *IOT enabled Smart Agriculture*	0.90	0.89	0.89

Table 1: Precision

The Recall of the above-mentioned experiments are discussed in Table 2.

Experiment Name	CNN+ LSTM	CNN+ BiLSTM	CNN+ GRU
a)Robotic arm Movement	0.90	0.89	0.89
b)*Fault detection in Electrical Circuits*	0.48	0.44	0.485
c) *IOT enabled Smart Agriculture*	0.87	0.88	0.87

Figure 2 : Recall

The F1 score of the above-mentioned experiments are discussed in Table 3.

Experiment Name	CNN+ LSTM	CNN+ BiLSTM	CNN+ GRU
a)Robotic arm Movement	0.92	0.91	0.91
b)*Fault detection in Electrical Circuits*	0.33	0.44	0.33
c) *IOT enabled Smart Agriculture*	0.88	0.88	0.87

Table 3 : F1 Score

From the above Tables 1,2,3, it could be concluded that the combination of CNN and BiLSTM performs better than other combinations of RNN models. The metrics of Fault detection are low due to the small dataset size.

V. FUTURE WORKS

The datasets available specific to electrical systems and robotics are very limited in terms of specific usage. To analyze and understand the limited dataset, in general, models go in the path of overfitting. Future work can include the generation of larger datasets of electrical systems for training models.

CONCLUSION

In recent trends, many organizations come up with machine learning integration. However, they lack a specific model to train in different electrical and electronic works. This research proposed a CNN+BiLSTM model for increasing efficiency in prediction. This paper investigates different combinations of convolution and recurrent neural network models and also saves a lot of time for researchers in finding the best model.

ACKNOWLEDGMENT

The dataset used in the experiments is available on open-source platforms such as Kaggle. The authors have no conflict of interest.

REFERENCES

[1] H. B. Mahajan et al., "Automatic robot Manoeuvres detection using computer vision and deep learning techniques: a perspective of internet of robotics things (IoRT)," *Multimedia Tools and Applications*, vol. 82, no. 15, pp. 23251-23276, Jun. 2023, doi: 10.1007/s11042-022-14253-5.

[2] G. H. Kang, K. S. Kim, C. Y. Chang, and C. S. Kim, "Fault Diagnosis of the Electric Multiple Unit Door System by Machine Learning Using Sensor Signal of the Simulator," *Journal of Electrical Engineering and Technology*, 2024, doi: 10.1007/s42835-024-02003-6.

[3] H. H. Huang, C. K. Cheng, Y. H. Chen, and H. Y. Tsai, "The Robotic Arm Velocity Planning Based on Reinforcement Learning,"

International Journal of Precision Engineering and Manufacturing, vol. 24, no. 9, pp. 1707-1721, Sep. 2023, doi: 10.1007/s12541-023-00880-x.

[4] I. R. Rodrigues et al., "A framework for robotic arm pose estimation and movement prediction based on deep and extreme learning models," *Journal of Supercomputing*, vol. 79, no. 7, pp. 7176-7205, May 2023, doi: 10.1007/s11227-022-04936-z.

[5] P. M. J. Ganesh, B. M. Sundaram, P. K. Balachandran, and G. B. Mohammad, "IntDEM: an intelligent deep optimized energy management system for IoT-enabled smart grid applications," *Electrical Engineering*, 2024, doi: 10.1007/s00202-024-02586-3.

[6] H. A. G. Al-kaf, J. W. Lee, and K. B. Lee, "Fault Detection of NPC Inverter Based on Ensemble Machine Learning Methods," *Journal of Electrical Engineering and Technology*, vol. 19, no. 1, pp. 285-295, Jan. 2024, doi: 10.1007/s42835-023-01740-4.

[7] L. Dai, B. Wang, X. Cheng, and Q. Wang, "The application of deep learning technology in integrated circuit design," *Energy Informatics*, vol. 7, no. 1, Dec. 2024, doi: 10.1186/s42162-024-00380-w.

[8] H. Xu and C. Jian, "A meta reinforcement learning-based virtual machine placement algorithm in mobile edge computing," *Cluster Computing*, vol. 27, no. 2, pp. 1883-1896, Apr. 2024, doi: 10.1007/s10586-023-04030-w.

[9] I. Attri, L. K. Awasthi, and T. P. Sharma, "Machine learning in agriculture: a review of crop management applications," *Multimedia Tools and Applications*, vol. 83, no. 5, pp. 12875-12915, Feb. 2024, doi: 10.1007/s11042-023-16105-2.

[10] A. Ullah, S. M. Anwar, J. Li, L. Nadeem, T. Mahmood, A. Rehman, and T. Saba, "Smart cities: the role of Internet of Things and machine learning in realizing a data-centric smart environment," *Complex and Intelligent Systems*, vol. 10, no. 1, pp. 1607-1637, Feb. 2024, doi: 10.1007/s40747-023-01175-4.

[11] A. Hundt, V. Jain, C.-H. Lin, C. Paxton, and G. D. Hager, "The CoSTAR Block Stacking Dataset: Learning with Workspace Constraints," in *2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2019. Available: https://arxiv.org/abs/1810.11714.